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A Comprehensive Survey on Artificial Intelligence - Based Classification of Gastrointestinal & Oesophageal Cancers

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ABSTRACT

The global incidence of Gastrointestinal (GI) disorders has risen dramatically over recent decades, driven chiefly by changes in dietary patterns and lifestyle behaviours; epidemiological evidence attributes nearly two million deaths annually to these conditions, underscoring their substantial burden on healthcare systems. Despite endoscopy's status as the diagnostic standard for detecting mucosal lesions—such as adenomatous polyps and oesophagitis—its performance is hindered by observer variability, limited reproducibility, and lengthy procedural times. To address these limitations, computer-aided diagnostic (CAD) frameworks have been integrated into clinical workflows, offering enhanced accuracy, throughput, and operational efficiency. AI-based pipelines leveraging advanced Machine Learning (ML) and Deep Learning (DL) architectures have proven highly effective in the early detection of GI malignancies and in quantitatively assessing tumour invasion depth. These technologies not only accelerate critical clinical decisions but also support the development of individualized, precision oncology regimens. This survey provides an in-depth assessment of current ML and ML methodologies applied to GI and oesophageal cancer diagnostics, evaluates established prognostic biomarkers, compares algorithmic performance metrics, and identifies key research directions to overcome existing methodological and translational challenges. Although AI-driven diagnostic systems hold the potential to transform GI oncology by standardizing workflows and improving detection rates, their routine clinical adoption requires rigorous validation in multicentre trials and the establishment of comprehensive implementation guidelines.

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1. INTRODUCTION

Gastrointestinal (GI) malignancies include tumors of the stomach, colon, rectum, and oesophagus. The World Health Organization reported roughly 3.5 million new GI cancer cases globally in 2018 [1]. Gastric carcinoma ranks fifth in incidence [2] and third in cancer-related mortality [3], whereas oesophageal cancer—although less common—carries a notably poor prognosis and high lethality [4]. Despite advances in therapeutics, prognostic and predictive biomarkers have not substantially reduced mortality in GI oncology, emphasizing the critical need for more effective diagnostic strategies [5, 6]. Biomarkers serve as molecular indicators of tumor presence, recurrence risk, therapeutic responsiveness, and overall disease trajectory [7]. However, supplementary molecular biomarker analyses frequently require additional tissue procurement, which increases operational costs and prolongs diagnostic timelines, posing significant challenges to clinical decision-making [8]. Chronic exposure of the mucosal lining to dietary and environmental carcinogens renders the GI system vulnerable to neoplastic transformation [9]. Consequently, GI cancers account for approximately 35% of global cancer-related mortality [10] and 26% of cancer incidence worldwide [11]. The recent surge in incidence and mortality rates is largely attributed to the increased prevalence of modifiable risk factors including obesity, poor dietary habits, sedentary lifestyles, and metabolic disorders [12, 13]. Notably, there has been an alarming rise in GI cancer incidence among individuals aged 25 to 49 years, highlighting a growing public health concern [14]. The five GI malignancies with the greatest global prevalence and impact are colorectal carcinoma, pancreatic adenocarcinoma, esophageal squamous cell neoplasm, hepatocellular carcinoma, and gastric adenocarcinoma [15]. Diagnosis and classification predominantly rely on histopathological examination of resected tumor specimens and endoscopic biopsy analyses [16]. Early detection remains challenging due to nonspecific initial symptoms, often resulting in clinical presentations at advanced stages [17,18].

Oesophageal cancer is one of the most diagnosed adenocarcinomas worldwide, with an estimated annual incidence of 500,000 new cases [19]. The prognosis remains poor, ranking as the sixth leading cause of cancer-related mortality globally [20]. The overall five-year survival rate is approximately 20%, varying significantly depending on disease stage. Localized esophageal cancer confined to the primary site shows a five-year survival rate around 46.4%, whereas distant metastatic disease is associated with survival as low as 5% [21]. The predominant histologic subtypes are esophageal adenocarcinoma (EAC) and esophageal squamous cell carcinoma (ESCC), together accounting for nearly 90% of cases [22]. While ESCC remains more prevalent in many regions, there has been a rising incidence of EAC in Western countries, including the United States [23]. Patients with EAC typically exhibit better median overall survival compared to those with ESCC, especially in early stages [24]. Risk factors for ESCC include alcohol use, tobacco consumption, male sex, and certain dietary habits; obesity and gastroesophageal reflux disease (GERD) are major contributors to EAC development [25, 26]. Barrett's esophagus, a premalignant condition, increases the risk of EAC by up to 40 times [27,28].

AI has emerged as a transformative paradigm in healthcare, accelerating digital innovation in clinical practice. It encompasses computational systems capable of mimicking human reasoning and performing tasks such as image analysis and pattern recognition by leveraging large-scale datasets [29]. ML, a subset of AI, involves training models iteratively on curated datasets to identify patterns and generate predictions for unseen data [30]. Representative ML algorithms include decision trees (DT), random forests (RF), support vector machines (SVM), and gradient boosting techniques (XGBoost) [31]. DL enhances these capabilities through multilayer artificial neural networks, capable of hierarchical feature extraction and excelling in high-dimensional applications like medical imaging [32]. The widespread adoption of electronic medical records (EMR) has generated vast clinical data repositories, which often exceed human analytic capacity, resulting in potential inefficiencies and diagnostic errors [33]. AI-driven methodologies offer scalable and reproducible analysis pipelines to process such data rapidly, yielding high-quality insights to support clinical decision-making [34]. Gastric and oesophageal malignancies present persistent clinical management challenges, with generally poor outcomes. Advancements in therapy have been achieved with minimally invasive surgical techniques combined with multimodal treatment regimens [35]. AI tools have demonstrated potential to mitigate postoperative complications by aiding in predicting responses to neoadjuvant chemoradiotherapy (nCRT), thus informing preoperative decisions [36]. Additionally, ML analysis of extensive surgical datasets facilitates personalized treatment planning and optimization of post-surgical recovery [37]. Despite these advances, ML application in gastric and esophageal cancer management remains relatively underexplored.

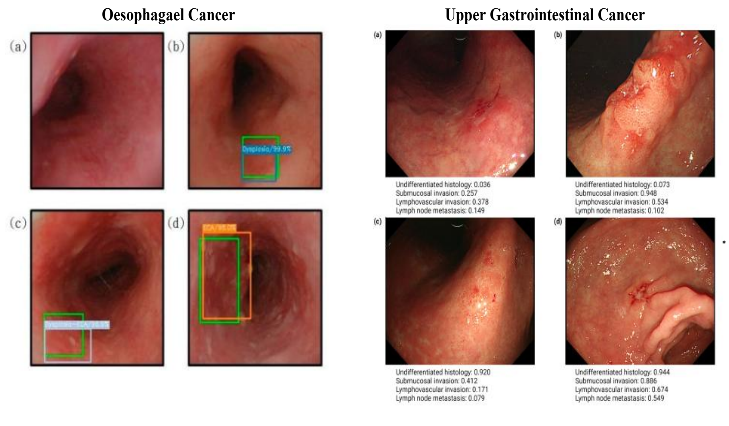

Figure 1. Detection of Oesophageal and GI Cancer via White-Light Endoscopic Imaging [37, 38].

AI's utilization in healthcare continues to grow, particularly in gastrointestinal endoscopy, as illustrated in Figure 1, derived from existing studies on esophageal and GI cancer prediction [38]. AI's superior pattern recognition capabilities hold promise for early detection of GI lesions and other abnormalities. However, data on AI-assisted GI and oesophageal cancer diagnosis remain limited. This survey aims to delineate AI-driven methods revolutionizing gastroenterology by enabling earlier detection and facilitating personalized treatment strategies based on endoscopic imaging analysis.

1.1 Novel Contributions

This survey provides three principal contributions to the field:

(i) **Comprehensive Feature Selection Analysis:** A thorough evaluation of filter, wrapper, and embedded feature selection methods specifically tailored to endoscopic imagery analysis.

(ii) **Advanced Architecture Assessment:** Comparative evaluation of leading deep learning models and transformer-based approaches for classification, detection, and segmentation tasks.

(iii) **Future Research Roadmap:** Identification of critical research gaps and systematic recommendations for next-generation AI-driven diagnostic systems.

2. ARCHITECTURE FOR AI-BASED GI AND OESOPHAGEAL CANCER DIAGNOSIS

A. Data Acquisition

A multimodal dataset is assembled, encompassing wireless capsule endoscopy (WCE) imagery, conventional endoscopic and radiological scans (e.g., CT, MRI), and digitized histopathological sections. Where available, patient demographics, laboratory values, and electronic health record variables supplement image-derived information to enrich model inputs.

B. Data Preprocessing

Raw image inputs undergo a sequence of enhancement operations—intensity normalization, artifact mitigation, contrast adjustment, histogram equalization, and noise attenuation—to optimize feature visibility. These steps counteract common artefacts such as poor illumination, specular glare, and occlusive artifacts.

C. Feature Extraction and Selection

Quantitative descriptors (texture, morphological, intensity, and spectral features) are computed to capture diagnostically salient patterns. Dimensionality is subsequently reduced via:

– Filter techniques (e.g., gain-ratio ranking) that score features independently of the learning algorithm.

– Wrapper methods (e.g., recursive feature elimination) that iteratively evaluate feature subsets.

– Embedded approaches that integrate selection within model optimization.

D. AI Task Framework

Algorithms are applied to three principal tasks:

Classification: assigning image regions or entire scans into neoplastic versus non-neoplastic categories,

Detection: localizing discrete lesions or abnormalities,

Segmentation: delineating lesion boundaries at the pixel level for precise morphological assessment.

E. Model Development

Selected features inform classical ML models—such as SVM, RF, and ensemble classifiers—for classification tasks. Concurrently, convolutional, and fully connected neural network architectures autonomously learn hierarchical representations from raw and preprocessed images to perform detection and segmentation. Classification networks ResNet, VGG, EfficientNet), detection frameworks YOLO, RCNN, and segmentation models UNet, DeepLab) process extracted features.

F. Optimization and Validation

Model hyperparameters are fine-tuned using metaheuristic strategies (e.g., artificial bee colony, particle swarm optimization) and genetic algorithms. Performance is rigorously assessed via k-fold cross-validation, with metrics including accuracy, sensitivity, specificity, area under the ROC curve, and precision-recall characteristics.

G. Clinical Decision Support

The validated models generate probabilistic outputs facilitating early tumor detection, stratification of patient risk profiles, and individualized treatment planning. Integration into clinical workflows enables automated reporting and decision-making support, thereby enhancing diagnostic consistency and patient management outcomes.

Figure 2 depicts the structured workflow for AI-based gastrointestinal and oesophageal cancer diagnosis. It begins with diverse data acquisition modalities, including wireless capsule endoscopy, CT, MRI, conventional endoscopy, histopathology, and clinical data such as demographics and lab results. The data undergo preprocessing for normalization, artifact correction, contrast adjustments, histogram equalization, and noise reduction. Critical features — texture, morphology, intensity, and spectral — are then extracted and selected using filter, wrapper, or embedded dimensionality reduction methods. The core AI tasks comprise classification, detection, and segmentation, implemented via machine learning and deep learning models, including detection and segmentation frameworks. Model optimization employs metaheuristic algorithms with cross-validation, validated by accuracy, sensitivity, and specificity metrics. Ultimately, the framework supports clinical decision-making through early tumor detection, risk stratification, treatment planning, and automated reporting, thereby enhancing diagnostic precision and patient management efficiency.

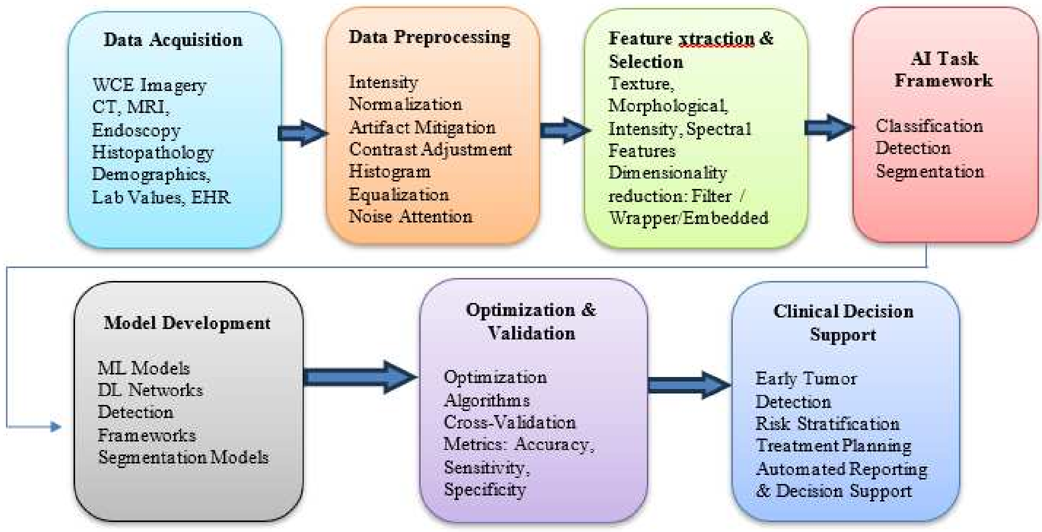

Figure 2. System Architecture

2.1 Existing Preprocessing and Feature Selection Methods

Endoscopic data—acquired via wireless capsule endoscopy (WCE) and conventional imaging modalities—undergo preprocessing to enhance diagnostically relevant traits and suppress noninformative noise. Unpruned feature sets often contain redundant or low-variance descriptors that degrade classification accuracy and inflate computational latency. Conversely, excessively large feature vectors increase model training and inference times without commensurate performance gains. To address these issues, contemporary GI image–based diagnostic pipelines incorporate multi-stage workflows comprising image normalization, artifact removal, and salient region extraction, followed by systematic feature selection to retain only high-impact variables. Typical preprocessing operations include contrast enhancement, histogram equalization, and speckle noise reduction, whereas feature selection strategies span filter-based ranking, wrapper-based search, and embedded methods. By excising nondominant features and focusing computational resources on the most discriminative signals, these approaches yield classification models that are both faster and more accurate, facilitating early detection of GI pathologies.

According to [39], a hybrid filter–wrapper feature selection approach was employed to identify pertinent gene signatures from oncological datasets. In this scheme, the wrapper component evaluates candidate feature subsets via iterative learning, thereby isolating the most informative genes and enhancing classifier performance, while the filter stage ranks feature independently of any induction algorithm. Although wrapper methods exhibit superior selection quality, their computational burden is high; this overhead is mitigated by prefiltering with gain-ratio ranking prior to wrapper evaluation. Specifically, gain ratio ranking (a ranker search strategy) was used to prune the initial gene pool, after which the Wrapper Subset Evaluator—utilizing a forward-selection heuristic within the WEKA environment—determined the optimal subset. In [40], a public colon-cancer gene-expression dataset (62 samples, 2,000 features) underwent dimensionality reduction via Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Conversely, applied Google's Auto Augment for dataset enrichment and employed Simple Linear Iterative Clustering (SLIC) super pixel segmentation alongside Fast and Robust Fuzzy C-Means (FRFCM) for image preprocessing [41].

Together, these methodologies have demonstrably improved the discrimination and classification of gastric malignancies relative to other gastric lesion types. In another study, the HyperKvasir labeled image dataset was partially utilized by [42] to focus on the identification of GI tract abnormalities, distinguishing pathological findings from normal anatomical landmarks. The dataset comprised both upper and lower GI images, which were aggregated into a single repository for processing. Initial dataset preparation involved resizing the raw images; this step revealed challenges such as low contrast, specular reflections manifesting as white spots or patches, and occlusions presenting as green or black regions. To address these issues, preprocessing operations—including image inpainting and contrast enhancement—were applied to improve image quality and ensure robust downstream analysis.

Optimization-focused investigations remain limited. In [43], a predictive model for dysplasia and oesophageal squamous cell carcinoma (ESCC) was developed, wherein established risk factors served as classifier inputs; the complex, nonlinear behavior inherent to tumor datasets yielded an optimized cost function. Conversely, [44] implemented a hybrid ensemble comprising support vector machines (SVM) and self-organizing maps (SOM) augmented by neural clustering. Receiver operating characteristic (ROC) analysis identified two survival-threshold cutoffs, enabling stratification of patient risk levels. Comparative evaluation of four SVM kernel functions demonstrated the radial basis function (RBF) kernel's superiority in predictive performance. Furthermore, SVM hyperparameters were tuned via Artificial Bee Colony (ABC), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) methods, with each optimization technique enhancing classification accuracy. Notably, the ABC-optimized SVM outperformed both PSO- and GA-tuned models, achieving higher prediction accuracy and reduced computation time. Research conducted by [45] implemented an ANN architecture in conjunction with a compound feature selection methodology that merged RF with Gray Wolf Optimization (RF-GWO) for the histological classification of colorectal malignancies. The approach demonstrated exceptional classification performance with an accuracy of 98.74%, primarily due to optimization-driven reductions in computational overhead, enhanced processing efficiency, and the broader solution space facilitated by the hybrid algorithmic framework.

Table 1. Comparative Analysis of AI Algorithm for GI Cancer Detection

S. No	Author	Dataset (Name & Size)	AI Model/Method	Feature Selection	Key Findings	Strengths/Limits
1	[39]	Oncological gene datasets	Hybrid filter-wrapper approach	Gain ratio ranking + Wrapper Subset Evaluator	Optimal gene subset identified improving classifier performance	Reduced computational cost via prefiltering
2	[40]	Public colon-cancer gene-expression (62 samples, 2 000 features)	Ensemble learning classifier	Dimensionality reduction via PCA + LDA	Achieved enhanced classification accuracy through lower-dimensional representation	PCA/LDA reduced noise; small sample size limits generalizability
3	[41]	Gastric endoscopic images (HyperKvasir subset, ≈10 000 images)	CNN with transfer learning	SLIC super pixel segmentation + Auto Augment image augmentation	Demonstrated superior lesion discrimination relative to conventional CNNs	Transfer learning improved feature extraction; augmentation increased training time
4	[42]	HyperKvasir labeled images	Image enhancement + SLIC + FRFCM	Image preprocessing	Improved detection of GI abnormalities	Handled occlusions and low contrast
5	[43]	ESCC risk factors	Predictive model with optimized cost function	Risk factors as classifier inputs	Nonlinear tumor behavior accurately modeled	New insights into ESCC progression

Table 1 illustrates a comparative analysis of various AI models used for GI cancer diagnosis. This synthesis provides insight into the evolving landscape of AI applications in GI oncology, highlighting methodological diversity and technological advancements aimed at improving early detection, diagnostic precision, and predictive capabilities.

Table 2. Performance Comparison of Optimization-Based Feature Selection Methods

S.No	Author	Objective	Methods used	Dataset used	Result	Advantages	Disadvantages
1.	[44]	Prediction of cancer survival risk	Feature Extraction, Classification: SVM, Self-Organizing Maps (SOM), Neural Clustering, Optimization with ABC, GA, PSO	Survival data with risk factors	Improved prediction accuracy with ABC-SVM best	Faster calculation, higher accuracy	Computational complexity for wrappers
2.	[45]	Histology classification of colorectal cancer	Feature Extraction, Classification: ANN classifier, Random Forest + Gray Wolf Optimization (RF-GWO)	Colorectal cancer histology data	Accuracy of 98.74%	Lower cost, reduced time, larger search space	Not specified
3.	[46]	Prediction of Gastric Cancer	Feature selection : Filter and wrapper based Classification: RF, SVM ML classifiers	Patient records from Shohadaye Tajrish Hospital & Shahid Ayatollah Modarres Hospital (2013-2021)	Achieved 95% accuracy using filter-wrapper method	Cost-effective, reduces physical complications in endoscopic image-based diagnosis	Limited dataset size, suggests more datasets needed
4.	[47]	Gastrointestinal (GI) Cancer Classification	Feature Extraction: Transfer Learning on pre- trained Classification: CNN model with African Vulture Optimization Algorithm (AVOA) .	Kvasir GI cancer medical image dataset	Accuracy of 99.64%	Improved accuracy and efficiency	Computationally intensive.
5.	[48]	Gastrointestinal (GI) Cancer Classification	Capsule Network (Capsnet) for feature extraction, Snake Optimization.	Kvasir multiclass GI cancer medical image dataset	Higher Accuracy of 99.72%	Preserves spatial hierarchies, more robust to rotational and affine transformation, Reduced overfitting higher accuracy, and precision	Higher Computational Cost, Requires More Training Time, Limited Scalability

The comparative analysis from Table 2 highlights that feature selection methods combined with CapsNet and Snake Optimizer achieve the highest accuracy of 99.72% for gastrointestinal cancer prediction. In contrast, the filter and wrapper-based feature selection techniques paired with machine learning classifiers exhibit a relatively lower accuracy of 95%. This suggests that optimization-driven deep learning models like CapsNet integrated with Snake Optimizer demonstrate superior performance compared to traditional feature selection and classification methods.

3. MACHINE LEARNING MODELS

ML techniques have been extensively applied to analyze complex multi-omics datasets for GI and oesophageal cancer diagnosis and prognosis. Wang et al. performed a comprehensive survey covering the utilization of standard ML algorithms such as RF, SVM, Logistic Regression (LR), and XGBoost to tackle the challenges posed by high-dimensional omics data including genomics, transcriptomics, and proteomics. The study highlighted feature extraction methods like Principal Component Analysis (PCA) as critical for dimensionality reduction, allowing robust classification performance by mitigating overfitting risks. The datasets analyzed spanned publicly available repositories with hundreds of patient samples, ensuring heterogeneity but also introducing batch effect challenges that remain a limitation [49].

[50] studies focused on endoscopic image analysis, utilizing annotated datasets exceeding 5,000 images for developing lesion detection models. They employed MLP and SVMs trained with image preprocessing and data augmentation techniques to enhance generalization. Their trained models achieved classification accuracies above 85%, demonstrating the potential of classical ML techniques in supporting clinical diagnostic workflows. However, the challenges of standardized image acquisition and high annotation costs limit the scalability and real-world applicability. [51] developed gastric cancer risk stratification models using a diverse dataset of approximately 1,500 patient records encompassing clinical and lifestyle variables. Six ML algorithms were evaluated, in which XGBoost and RF yielded the highest predictive accuracy with AUROC values nearing 0.90. By comparing multiple algorithms, the study identified ensemble methods as superior for capturing complex patterns in heterogeneous patient data. Limitations include the retrospective study design and potential biases inherent in electronic health record data.

[52] utilized multicenter cohort data from rural China including nearly 10,000 participants to construct a logistic regression model for esophageal cancer risk. Incorporated variables spanned demographic factors, family history, pain symptoms, nutritional aspects, and age. An AUROC of 0.81 was achieved, indicating high predictive value suitable for population-level screening. While sample size and diverse clinical factors strengthen this work, reliance on regional cohorts and self-reported data could constrain generalizability. [53,54] extended risk models by integrating behavioral risk factors including smoking habits, levels of physical activity, body mass index (BMI), and alcohol intake data, achieving AUROCs around 0.76 through internal validation. The studies underscore lifestyle determinants as significant contributors to GI and esophageal cancer susceptibility. Data quality issues, such as recall bias and missingness, remain methodological challenges.

[55] conducted a rigorous benchmarking study comparing classical statistical methods such as LR, logistic regression, and variance analysis—with ML algorithms including random forest, support vector machines, and multilayer perceptron's across multiple large clinical datasets. Utilizing five-fold cross-validation and hyperparameter optimization, they demonstrated that machine learning methods achieved 10–15% higher predictive accuracy on tasks such as postoperative complication risk and recurrence prediction. The study highlighted machine learning's ability to capture complex nonlinear interactions and manage missing values through ensemble imputation, though it noted that the resultant models exhibited reduced interpretability and required substantially greater computational resources.[56] evaluated the prognostic utility of machine learning models for five-year survival prediction in a cohort of 2,350 oesophageal cancer patients. They compared ensemble methods—RF and XGBoost—with traditional Cox proportional hazards models. With an optimized feature set encompassing 25 clinical and pathological variables, the random forest model achieved an AUROC of 0.87, and the gradient boosting model reached 0.89, outperforming the Cox model's AUROC of 0.78. Feature importance analyses revealed interactions between tumor stage, patient age, and nutritional biomarkers as key drivers of prognosis. While these findings underscore machine learning's enhanced risk stratification, the authors cautioned that retrospective data and the absence of external validation limit immediate clinical translation.

Research conducted in [57] implemented a radiomic feature-based ML architecture for prognostic modeling of overall survival and disease-free survival among 412 oesophageal cancer patients receiving concurrent chemoradiotherapy without surgical intervention. High-dimensional radiomic features—comprising advanced texture metrics, shape descriptors, and intensity histograms—were extracted from baseline CT scans. After recursive feature elimination, sixteen radiomic signatures were integrated into support vector machine and random forest classifiers. The RF model achieved a concordance index of 0.78 for overall survival and 0.76 for progression-free survival, surpassing the TNM staging system's C-index of 0.65. The study emphasized non-invasive prognostication and personalized treatment planning, while noting challenges related to inter-scanner variability, the need for standardized imaging protocols, and prospective multicentre validation to ensure robust generalizability. [58] reviewed ML applications for therapy optimization, prognostic evaluations, and survival prediction in GI cancers. The paper identified issues of data heterogeneity, lack of reproducibility, and ethical/regulatory concerns as major obstacles to clinical adoption. This comprehensive review calls for standardized data pipelines and transparent model explanations to facilitate safe and effective application.

Table 3. Performance Evaluation of ML Models for GI and Oesophageal Cancer Detection

S. No.	Author	Objective	Methods used	Dataset used	Result	Strengths	Limitations
1.	[59]	Oesophageal adenocarcinoma predictive model	Feature Extraction: Regression (ELR)- Classification: ML approaches- XGB and RF	International data set = total of 812 patients.	Accuracy of 80.5 % for ELR, RF, XGB	Provides reliable estimation of early postoperative recurrence risk. Facilitates prognostic guidance for both clinicians and patients.	High proportion of missing data for key outcomes. Lack of external validation dataset.
2.	[60]	Classification of oesophagitis and Barrett's oesophagus	Feature Extraction: ResNet50–based CNN model Classification: SVM	Kvasir dataset	Accuracy of 94.46%	Better performance in early detection of recurrence.	Accuracy depends on the quality of clinical data
3.	[61]	Predict curative treatment decisions	Feature Extraction: Logistic Regression (MLR), XGB and RF and DT Classification: Classical Regression	Oesophagectomy database from 2010 to 2020	Accuracy of 79.30%	Provide insight into cancer care decision-making	For optimal fine tuning may require larger dataset.
4.	[62]	Hepatic Metastasis Prediction in oesophageal cancer.	Feature Extraction: : RF, GB, XGB Classification: ensemble classifiers LR, DT, Naive Bayes classifiers.	SEER from 2010 to 2020.	86.08% Accuracy	Facilitates expert clinical decision making for optimized treatment planning.	Integration of multicenter datasets for model training and subsequent external validation improves the model robustness and generalizability.
5.	[63]	Diagnosis of Oesophageal Cancer Metastasis	Feature Extraction: CatBoost based ML model	TCGA	73% accuracy	Metastasis prediction enhanced with minimized reliance on invasive diagnostics.	Accuracy can be improved.

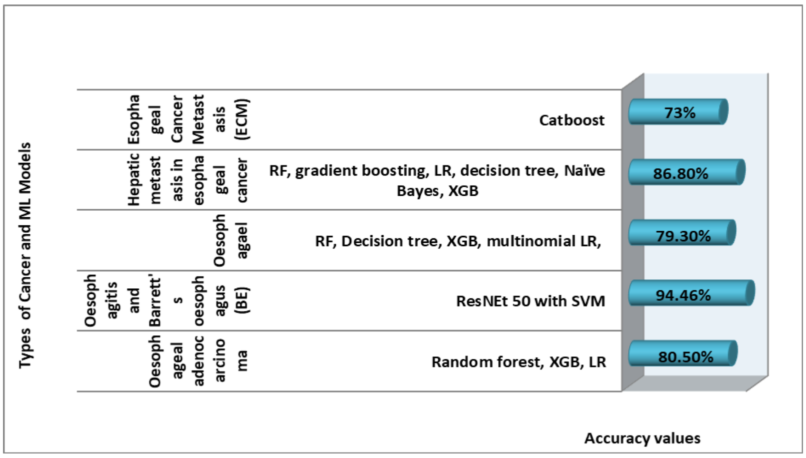

Figure 3. Performance Evaluation of ML Models for GI and Oesophageal Cancer

Figure 3 and Table 3 present a comparative analysis of ML model performances across various GI cancers. Notably, the ResNet-50 combined with an SVM classifier achieved the highest accuracy of 94.46%, whereas the CatBoost-based ML algorithm yielded a substantially lower accuracy of 73%.

4. DEEP LEARNING MODELS

Accurate cancer diagnosis remains a critical challenge in biomedicine. Recent advances in AI, specifically DL and ML algorithms, have significantly enhanced diagnostic capabilities. Modern models can automatically extract insightful features from high-dimensional data, outperforming traditional DL models such as CNNs and FCNNs. DL methods demonstrate superior performance in diagnosing GI and oesophageal cancers across various evaluation metrics. The generalizability of DL models is enhanced when validated across diverse datasets, and accurate diagnostic performance can assist physicians in earlier oesophageal cancer detection, potentially reducing mortality rates. Previously, early identification relied heavily on the expertise of endoscopists. However, DL models exhibiting elevated sensitivity and specificity enable precise detection of esophageal carcinoma, thereby facilitating timely therapeutic decision-making and improving patient prognoses.

In study [64], a systematic review and meta-analysis of sixteen investigations assessed AI-assisted endoscopic detection of esophageal cancer and neoplasms, reporting a pooled sensitivity of 94% (95% CI: 92%–96%), specificity of 85%, and an AUROC of 0.97. The meta-analysis revealed that AI-based models significantly outperformed endoscopists in sensitivity (94% vs 82%, $P < 0.01$), highlighting the superior capability of AI systems in detecting subtle oesophageal lesions that might be missed by human observation.

Study [65] conducted a systematic review and meta-analysis of AI-assisted detection of upper gastrointestinal lesions using multicentre datasets. Their evaluation, encompassing cohorts of several hundred to thousands of endoscopic images, reported diagnostic accuracies consistently exceeding 90% across diverse imaging modalities and patient populations. The analysis underscored the robustness of convolutional neural network (CNN) architectures in discriminating benign, precancerous, and malignant tissue types.

In study [66], researchers performed a meta-analysis on computer-aided diagnosis for oesophageal cancer and related neoplasms in endoscopic imaging. This investigation compared deep learning models with traditional machine learning classifiers, highlighting AI's superior reproducibility and consistency relative to human endoscopists. Key limitations identified included the requirement for high-quality annotated image repositories and the need for uniform imaging acquisition protocols. Further emphasized that XAI frameworks are essential for clinical acceptance and regulatory endorsement.

Study [67] provided a comprehensive synthesis of CNN-based AI performance in gastrointestinal lesion diagnosis. Pooled sensitivity and specificity metrics surpassed 90% for early lesion detection, with validated performance across white-light imaging (WLI), narrow-band imaging (NBI), and magnifying endoscopy. Practical considerations—such as computational load, real-time processing feasibility, and compatibility with existing endoscopic systems—were also addressed.

Collectively, these meta-analyses furnish compelling evidence that AI-augmented endoscopic evaluation significantly improves detection rates for oesophageal malignancies and precursor lesions, achieving higher sensitivity than conventional endoscopist evaluations without sacrificing specificity. Nonetheless, critical research gaps persist: prospective multicentre trials are needed for robust validation, standardized imaging protocols must be established, XAI models should be developed, and clear regulatory pathways are required to enable clinical deployment.

Table 4. Comparative Analysis of DL Models for GI and Oesophageal Cancer Diagnosis

S. No.	Author	Objective	Methods used	Dataset used	Result	Strengths	Limitations
1	[68]	Automated diagnosis of gastric cancer	Feature Extraction: DLU-Net, Classification: CNN	3,591 gastroscopy images (training and validation sets)	94.1% classification accuracy	Identifies staging characteristics, supports clinical decision-making in GC diagnosis	Detailed disadvantages not specified
2.	[69]	Diagnosis of oesophageal cancer	Feature Extraction: Fine-tuned VGG16; Classification: CNN-based recognition	457 patient samples (2005–2018)	84.2% classification accuracy	Enhanced diagnostic accuracy and decision support	Dataset size limited; temporal features not fully captured
3.	[70]	"T" stage assessment of oesophageal cancer	Feature Extraction, Classification: EfficientNetB7, ResNet152V2	Clinically diagnosed EC patients' records	Accuracy of 90%	Improved staging accuracy; aids clinical decisions	Further validation on larger datasets recommended

S. No.	Author	Objective	Methods used	Dataset used	Result	Strengths	Limitations
4.	[71]	Early detection of oesophageal cancer	Feature Extraction, , Classification: YOLO framework	CVC Clinic DB, Kvasir-SEG, EEC 2022	90–94% accuracy	Reduces overfitting; superior estimation precision	Dataset limited; precision may require enhancement
5.	[72]	Early detection of oesophageal cancer	Feature Extraction, , Classification: ResNet, VGG, EfficientNet,DLU-Net, YOLO, FCNN, Capsule Networks	Aggregated data from PubMed, EMBASE, Cochrane, Google, and CNKI (pre-Aug 2023)	97% accuracy	Demonstrates great potential of AI systems for EC diagnosis; documents methodological novelty	Additional comparative studies required

The comparative data from Figure 4 and Table 4 indicate that deep learning models achieve superior diagnostic accuracy for gastrointestinal cancers, reaching up to 97%, whereas the fine-tuned VGG-16 combined with CNN attains a lower accuracy of 84.2%. This underscores the enhanced efficacy of advanced DL models in cancer detection tasks.

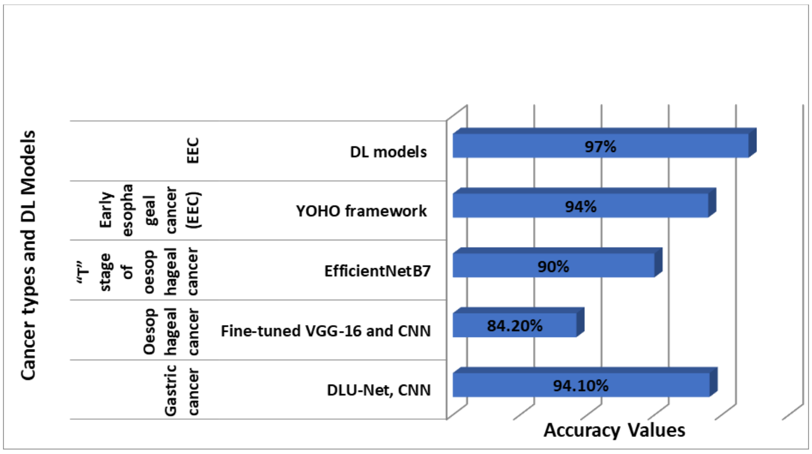

Figure 4. Comparison of DL Models for GI and Oesophageal cancer

5. RESEARCH DISCUSSION

Cancer remains a leading cause of mortality worldwide. This survey focuses on GI cancers, emphasizing early diagnostics aided by AI through ML, DL, and optimization algorithms. GI cancers often originate from abnormal tissue growths known as polyps on the mucosal linings of the colon and stomach. These polyps may proliferate slowly, with symptoms manifesting only once they attain significant size. Crucially, timely detection enables intervention to prevent progression and even cure the disease at an early stage. Endoscopic video imaging plays a pivotal role in early GI cancer detection by capturing mucosal patterns and identifying conditions such as ulcerative colitis, which exhibit spatial variations in texture and color corresponding to mucosal roughness. However, an endoscopy session can generate hundreds of frames, among which only a fraction may display pathological changes. Manual inspection by medical professionals is both time-intensive and subject to observer variability, potentially resulting in missed diagnoses whether due to fatigue or other human factors.

Automated AI-based diagnostic platforms mitigate the risk of misclassification or delayed detection by enabling high-throughput analysis of extensive endoscopic and clinical datasets. Advanced machine learning and deep learning models extract intricate microarchitectural patterns that elude human perception, reliably distinguishing neoplastic from non-neoplastic tissue. Cutting-edge feature extraction and selection methodologies—enhanced by recent algorithmic innovations—have been applied to identify prognostic gastric cancer biomarkers. Nonetheless, pinpointing and isolating the most discriminative image features remains challenging, often undermining classification accuracy. In this context, optimization algorithms play a pivotal role by refining feature engineering pipelines, enhancing separability, and strengthening overall diagnostic performance.

Early-stage identification of oesophageal carcinoma is critical for enhancing patient survival, as advanced presentations often require multimodal interventions such as chemoradiotherapy and surgical resection. DL frameworks applied to endoscopic image analysis have attracted considerable attention for supplementing physician diagnostics in real-world clinical workflows. However, rigorous benchmarking against established clinical criteria is essential to validate these models' accuracy and reliability. While DL excels at extracting visual features, comprehensive diagnosis necessitates the integration of heterogeneous data streams—including laboratory results, patient histories, and multimodal imaging—to achieve robust predictive performance. Fusion algorithms capable of uniting these diverse data modalities remain under active investigation in GI oncology research. Emerging holistically interpretable architectures aim to deliver transparent decision support, enabling tailored therapeutic strategies. Continued advancement in model explainability and multimodal data harmonization will be pivotal for translating AI-driven diagnostics into personalized cancer care.

Certain key implications of this survey are,

- ML and DL algorithms can significantly enhance the early detection GI and oesophageal cancers leads to timely earlier diagnosis and better patient outcomes.
- The optimization-based ML and DL algorithms can increase the accuracy and reliability of GI and oesophagael diagnosis.
- By evaluating larger datasets of GI cancers, ML and DL algorithms can supports in the development of personalized treatment plans which improves treatment efficiency.

5.1 Research Gaps

Despite significant advances, GI cancer screening systems face several limitations:

- Overreliance on endoscopic imaging with insufficient integration of clinical laboratory, genomic, and patient history data restricts diagnostic scope.
- Feature extraction methods require further refinement to improve sensitivity and specificity.
- Regulatory hurdles and protracted approval processes impede clinical adoption of AI tools.
- Public datasets suffer from small size, demographic imbalances, and inconsistent labeling, limiting model robustness.
- Real-time inference demands optimized, low-latency computing hardware, which currently remains underdeveloped.

5.2 Implementation Suggestions

Implementation should proceed along several technical priorities. First, comprehensive multimodal AI architectures must be engineered to fuse high-resolution endoscopic video with quantitative laboratory assays, genomic profiles, and structured electronic health record variables, thereby enabling integrated risk stratification and diagnostic inference. Second, the deployment of advanced optimization strategies—such as metaheuristic search algorithms and gradient-driven feature refinement—will be critical to identify and select the most diagnostically salient image and clinical features within high-dimensional data spaces. Third, XAI methodologies—such as SHapley Additive explanations and Local Interpretable Model-Agnostic Explanations—should be integrated throughout model development to elucidate decision pathways, promote clinician trust, and satisfy regulatory transparency requirements. Fourth, early and sustained collaboration with regulatory authorities is essential to align development workflows with medical-device frameworks, reducing approval timelines and ensuring compliance with safety standards. Fifth, the establishment of extensive, consortium-curated imaging repositories with uniform annotation schemas will facilitate robust algorithm training, cross-institutional benchmarking, and external validation across heterogeneous patient cohorts. Finally, integration of computationally efficient AI modules—including specialized neural processing accelerators—into endoscopic platforms will enable real-time, on-device inference and automated diagnostic alert generation during procedures, thus improving procedural throughput and diagnostic consistency.

6. CONCLUSION AND FUTURE SCOPE

The survey demonstrates that AI-driven frameworks significantly advance early detection of GI malignancies and support efficient clinical decision-making. Deep neural network models consistently outperform conventional machine learning approaches in classifying endoscopic images and video sequences, enabling seamless integration into existing workflows while reducing manual review burdens. However, large-scale, multicenter clinical trials are essential to confirm robustness and generalizability across diverse patient populations. Regulatory classification of AI tools as medical devices necessitates comprehensive safety and efficacy evaluations, and the current lack of large, heterogeneous imaging datasets poses a risk of biased performance. Strict adherence to data governance and privacy standards remains critical throughout model development and deployment. The integration of radiomic analyses with three-dimensional mucosal mapping and the adoption XAI techniques such as saliency heatmaps and decision-path visualizations promise to enhance lesion characterization and foster clinician trust. Continued efforts in dataset expansion, rigorous validation, and explainability will underpin the translation of AI-enabled diagnostics into precision endoscopy for gastrointestinal oncology.

Future research in AI-driven gastrointestinal cancer screening should emphasize the development of computationally efficient, low-latency deep learning architectures optimized for deployment on resource-constrained endoscopic platforms to enable real-time lesion detection. These architectures must incorporate advanced convolutional and transformer-based modules tailored for on-device inference, balancing model complexity with inference speed and power consumption. Concurrent advancements are required in three-dimensional reconstruction algorithms that integrate sequential endoscopic video frames with spatially calibrated sensor metadata, thereby facilitating volumetric and morphometric analysis of mucosal pathology with enhanced spatial accuracy. To ensure clinician trust and regulatory compliance, it is imperative to embed XAI methodologies within these systems. This includes saliency mapping, counterfactual explanations, and pathway attribution techniques that elucidate the decision-making processes and feature importance in model predictions, thereby enhancing interpretability and facilitating clinical validation. Diagnostic workflows should transition toward adaptive, patient-specific paradigms by integrating phenotypic, genomic, and lifestyle risk factors, enabling tailored surveillance strategies that optimize diagnostic yield and resource allocation. Implementation within Internet-of-Things (IoT)-enabled endoscopic frameworks necessitates the integration of edge-computing modules capable of performing distributed inference and triggering automated alerts during endoscopic examinations without reliance on continuous network connectivity. Simultaneously, continuous remote monitoring through networked capsule endoscopes and wearable biosensors will provide longitudinal physiological and behavioural data streams for centralized analytics and predictive modelling.

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All the data is collected from the simulation reports of the software and tools used by the authors. Authors are working on implementing the same using real world data with appropriate permissions.

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Author 1: Performed the Analysis the overall concept, writing and editing.

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